The EPIC Architecture for Modeling Human Information-Processing and Performance: A Brief Introduction

David E. Kieras
Artificial Intelligence Laboratory
Electrical Engineering & Computer Science Department
University of Michigan

David E. Meyer
Department of Psychology
University of Michigan
330 Packard Road, Ann Arbor, MI 48104

University of Michigan

EPIC Report No. 1 (TR-94/ONR-EPIC-1)

April 1, 1994

This research was supported by the Office of Naval Research, Cognitive Science Program, under Grant Number N00014-92-J-1173. Grant Authority Identification Number NR 4422574. Reproduction in whole or part is permitted for any purpose of the United States Government.

REPORT DOCUMENTATION PAGE	Form Approved OMB No. 0704-0188

1. AGENCY USE ONLY (*Leave blank*)	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	April 1, 1994	Interim Jan 1, 1992-April 1, 1994

4. TITLE AND SUBTITLE
The EPIC Architecture for Modeling Human Information-Processing and Performance: A Brief Introduction.

5. FUNDING NUMBERS
G N0014-92-J-1173
PR 4422574

6. AUTHOR(S)
David E. Kieras & David E. Meyer

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
University of Michigan
Division of Research development and administration
Ann Arbor, MI 48109-1274

8. PERFORMING ORGANIZATION REPORT NUMBER
TR-94/ONR-EPIC-1

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Cognitive Science Program (342 CS)
Office of Naval Research
800 N. Quincy St.
Arlington, VA 22217-5660

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for Public Release; Distribution Unlimited

12b. DISTRIBUTION CODE

13. ABSTRACT (*Maximum 200 words*)

EPIC (Executive Process-Interactive Control) is a human information-processing architecture that is especially suited for modeling multiple-task performance. The EPIC architecture includes peripheral sensory-motor processors surrounding a production-rule cognitive processor, and is being used to construct precise computational models for basic multiple-task situations. Some of these models are briefly illustrated here to demonstrate how EPIC applies to multiple-task performance, and helps clarify some basic properties of human performance. Additional applications of EPIC to modeling human-computer interaction are briefly summarized.

14. SUBJECT TERMS	15. NUMBER OF PAGES
Human performance, Cognitive Models, Human-Computer Interaction	19+
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	

The EPIC Architecture for Modeling Human Information-Processing and Performance: A Brief Introduction

David E. Kieras
Artificial Intelligence Laboratory
Electrical Engineering & Computer Science Department

David E. Meyer
Department of Psychology

University of Michigan

ABSTRACT

EPIC (Executive Process-Interactive Control) is a human information-processing architecture that is especially suited for modeling multiple-task performance. The EPIC architecture includes peripheral sensory-motor processors surrounding a production-rule cognitive processor, and is being used to construct precise computational models for basic multiple-task situations. Some of these models are briefly illustrated here to demonstrate how EPIC applies to multiple-task performance, and helps clarify some basic properties of human performance. Additional applications of EPIC to modeling human-computer interaction are briefly summarized.

INTRODUCTION

This report is a brief introduction to the EPIC architecture for human information processing, which is being developed under ONR sponsorship. Additional reports now in preparation will provide considerably more detail on the architecture and its application to specific modeling domains in human multiple-task performance and human-computer interaction.

The goal of the EPIC project is to develop a comprehensive computational theory of multiple-task performance that (a) is based on current theory and results in cognitive psychology and human performance; (b) will support rigorous characterization and quantitative prediction of the mental workload and performance, especially in multiple-task situations; and (c) is useful in practical system design.

The orientation of the EPIC project toward practically useful prediction is important because proposals for cognitive theories that are indeed useful in practical system design are unusual. The best known previous attempt is the Model Human Processor (MHP) proposed by Card, Moran, and Newell (1983). The MHP is a remarkable synthesis of cognitive theory and empirical data based on the key insight that results from experimental psychology can be cast in the form of a simplified model with parametric properties. Such a model, if properly constructed, can serve as an *engineering model*, a model both simple and quantitatively accurate enough to be useful in the design of systems, such as computer user interfaces. The work of Gray, John, and Atwood

(1992) in which tasks are analyzed in terms of sequential and parallel MHP processes shows that this class of model can indeed be used for engineering analysis and design. However, our effort to construct computational models based on a more recent and more thorough examination of empirical results makes it clear that the MHP is both incomplete and incorrect in many significant respects.

EPIC was designed to explicitly couple the basic information processing and perceptual-motor mechanisms represented in the MHP with a cognitive analysis of procedural skill, namely that represented by production-system models such as Cognitive Complexity Theory (CCT, Bovair, Kieras, & Polson, 1990, ACT (Anderson, 1976), and SOAR (see Peck & John, 1992). Thus, EPIC has a production-rule cognitive processor surrounded by perceptual-motor peripherals; applying EPIC to a task situation requires specifying *both* the production-rule programming for the cognitive processor, and also the relevant perceptual and motor processing parameters.

The EPIC model is thus in same spirit as the MHP, but there are several key differences. First, relative to the MHP, we have used more recent and detailed empirical evidence, especially concerning multiple-task performance, to define the mechanisms in the EPIC architecture. The result is that all of the processors in EPIC have fundamental differences from those in the MHP; in particular, the motor processors are much more elaborated, and the cognitive processor is implemented as a production system whose rules represent how the system performs the task. Second, unlike the original MHP presentation, we have adopted a rigorous theoretical approach consisting of constructing and testing computational models and subjecting them to detailed quantitative comparison with data. Constructing such models involves a detailed task analysis of the experimental task, which is usually overlooked in conventional psychological theorizing, but is a key advantage of the computational model approach (see Kieras, 1990). Third, in comparison with the Gray, John, and Atwood (1992) models, our computational models are generative; that is, in the model, a simulated human with general procedural knowledge of the task interacts with a simulated task environment, and so the model generates the sequence of serial and parallel processes in the course of performing the task. Thus the task analysis reflected in the model is constrained to be general to a class of tasks, rather than reflecting specific task scenarios.

Much of our focus is on multiple-task performance, in which the human is trying to concurrently execute a set of tasks; the tasks are independent, in that each could be meaningfully described and conducted in isolation. A good example of a multiple-task situation is the airplane cockpit. In a multiple-task situation, the main problem confronting the human is to execute the independent tasks in a coordinated fashion that meets some constraints on overall performance, such as giving one task priority over the other. We have focused on multiple-task performance for two reasons: First, it is of great practical importance, but is theoretically underdeveloped. Second, the multiple-task situation stresses human capabilities very seriously, and so the patterns of experimental effects set very strong constraints on the human information-processing system architecture. Thus our analyses of even simple multiple-task situations have resulted in detailed hypotheses about human information processing mechanisms that are represented in the EPIC architecture.

THE EPIC ARCHITECTURE

System Structure and Principles

This is a preliminary report, so our presentation and justification of the architecture must be severely limited; a more detailed presentation appears in forthcoming reports, one that will provide a fully detailed view of the architecture, and another that will more completely describe the specific models presented below.

Figure 1 shows the overall structure of processors and memories in the EPIC architecture. At this level, EPIC is rather conventional, and closely resembles the MHP. However, there are some important new concepts in the EPIC architecture that this brief presentation will highlight.

As shown in Figure 1, there is a conventional flow of information from sense organs, through perceptual processors, to a cognitive processor (consisting of a production rule interpreter and a working memory), and finally to motor processors that control effector organs. Some new features relative to the older MHP proposal (Card, et. al, 1983) are as follows: There are separate perceptual processors with distinct processing time characteristics, and more motor processors, especially the ocular motor processor that controls where the eye is looking. There are feedback pathways from the motor processors, as well as tactile feedback from the effectors, which is important in coordinating multiple tasks. The declarative/procedural knowledge distinction of the "ACT-class" cognitive architectures (see Anderson, 1976) is represented in the form of separate permanent memories for production rules and declarative information. At this time, we do not propose specific properties of the working memory (WM) because clarifying what types of working memory systems are used in multiple-task performance is one of our research goals; in the meantime, WM contains all of the temporary information tested for and manipulated by the production rules, including control information such as task goals and sequencing information, and also conventional working memory items, such as representations of sensory inputs.

A single stimulus input to a perceptual processor can produce multiple outputs to be deposited in WM at different times. The first output is a representation that a perceptual event has been detected, followed later by a representation that describes the recognized event. For present purposes, we assume that the mean detection time is fixed, estimated at 100 ms for visual events and 50 ms for auditory, while the recoding process takes additional time after the detection process, and depends on the properties of the stimulus. For example, recognizing letters on screen in a typical experiment might take on the order of 150 ms after the detection time. At present, we have estimated these recognition times from the empirical data being modeled.

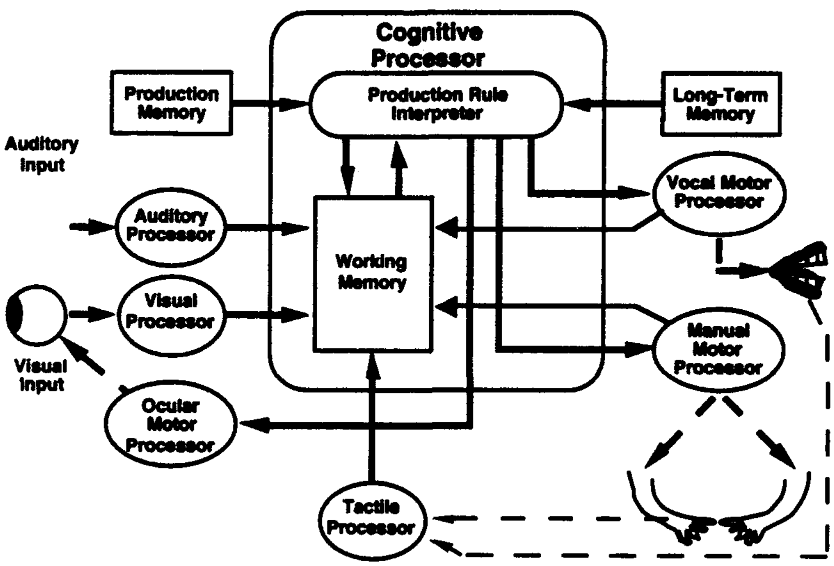

Figure 1. Overall structure of the EPIC architecture showing information flow paths as solid lines, mechanical control or connections as dotted lines.

The cognitive processor is programmed in terms of production rules, and so in order to model a task, we must supply a set of production rules that specify what actions in what situations must be performed to do the task. We are using the interpreter from the Parsimonious Production System (PPS) which is especially suited to task modeling work (see Bovair, Kieras, & Polson, 1990). One important feature of PPS is that control information such as the current goals is simply another type of WM item, and so can be manipulated by rule actions. A critical difference with the MHP is that on each cognitive processor cycle, any number of rules can fire and execute their actions; this parallelism is a fundamental feature of PPS. The cognitive processor accepts input only at the beginning of each cycle, and produces output at the end of the cycle, whose mean duration we estimate at 50 ms. Thus, unlike the MHP, the EPIC cognitive processor is not constrained to be doing only one thing at time. Rather, multiple processing threads can be represented simply as sets of rules that happen to run simultaneously.

An important difference with the MHP involves the basic temporal relationships of the processors. The perceptual processors in EPIC are "pipelines," in that an input produces an output at a certain later time, independently of what particular time it arrives. However, the cognitive processor accepts input only every 50 ms, and is constantly running, not synchronized with external events. This means that perceptual processor output to the cognitive processor must wait an average of 25 ms until it is accepted. Thus the temporal resolution on sensory events is limited centrally, rather than reflecting temporal integration by the perceptual processors, as proposed in the MHP. Our proposal, along with the 50 ms cognitive cycle time, is supported nicely by work on human simultaneity judgments (Kristofferson, 1967).

The EPIC motor processors are much more elaborate than those in the MHP. Certain results (e.g., McLeod, 1977) motivate our assumptions that the motor processors operate independently, but the hands are bottlenecked through a single manual processor. Thus, the hands normally cannot be controlled independently; rather they can be operated either one at a time, or synchronized with each other. Current research on movement control (e.g., Rosenbaum, 1980) suggests that movements are specified in terms of features, and the time to produce a movement depends on its feature structure as well as its mechanical properties. We have represented this property in highly simplified models for the motor processors. The input to the motor processors consist of a symbolic name for the desired movement, or movement feature. The processor recodes the symbol into a set of movement features, and then initiates the movement. The external device will then detect the movement after some additional mechanical delay. For example, using our estimates, if the desired movement is to press a button with the right-hand index finger, the symbolic name would be recoded into the movement features <RIGHT, INDEX>, taking an average of 50 ms each, followed by 50 ms for the movement initiation, and a final 10 ms for the mechanical motion of pressing the button.

An important empirical result is that effectors can be preprogrammed if the movement can be anticipated (Rosenbaum, 1980). In our model, this takes the form of instructing the motor processor to generate the features, and then at a later time instructing the movement to be initiated. As a result of the pre-generation of the features, the resulting movement will be made sooner.

We simulate task performance by simulating the human interacting with the task environment in simulated real time, in which the processors run independently and in parallel. We include a process that represents the task, and which generates stimuli and collects the responses and their simulated times over a large number of trials. To represent human variability, the processor time parameters are varied stochastically about their mean values with a regime that produces a coefficient of variation for simple reaction time of about 20%, which is a typical empirical value.

A Comparison of EPIC with MHP

The similarities and differences between EPIC and the MHP can be illustrated by how the two architectures produce approximately the same prediction of the time for a simple reaction task. In the simple reaction task, the subject simply makes a response (e.g. pushing a button with the index finger) when a stimulus appears (e.g. a single light comes on), where there is only one possible stimulus and response. For both architectures, it takes 100 ms to detect the stimulus; in a simple reaction time task, it is not necessary to recognize or recode the stimulus before making a response, which would take longer in the EPIC architecture. Both architectures would require only a single cognitive cycle to select the response to the stimulus. The MHP assumes that a cycle is nominally 70 ms; in EPIC, the perceptual output must wait an average of 25 ms before being accepted by the cognitive processor, and then it takes 50 ms for the cognitive cycle to complete, for a mean total of 75. The MHP would require only a single motor cycle of 70 ms to produce the response; in EPIC, because the response in a simple reaction task can be prespecified, the movement features can be generated in advance, and only the movement initiation time of 50 ms followed by the mechanical time, estimated at 10 ms, is required for making the response, for a total of 60 ms. Thus the MHP requires a total of 100+70+70=240 ms for a simple reaction; the EPIC architecture requires the essentially identical 100+75+60=235 ms.

Of course with more complex tasks and strategies, the two architectures will not look so similar. The differences begin to appear even for the very simplest choice reaction or tracking tasks. In fact, the two architectures are not really comparable for complex tasks and situations because fundamentally different mechanisms come into play. For example, the MHP does not include a motor feature mechanism, nor differential times for auditory vs. visual detection and recognition times. More importantly, in EPIC the cognitive processor must be explicitly programmed with production rules in a specified format; this property of the MHP is only suggested in Card, Moran, & Newell (1983). Thus, while similar in structure and spirit to the MHP, the EPIC framework operates at a much more detailed and specific level of analysis, and with a explicit computational representation of the task.

Rationale for EPIC's Basic Assumptions

The literature on multiple-task performance is extensive, and will not be summarized here. (for a review, see Gopher & Donchin, 1986). Of course human information processing is limited in capacity, and it has been traditionally assumed that there is a single-channel bottleneck (Welford, 1952). But humans can do multiple tasks, sometimes impressively well, and their ability to do so depends strongly on the specific combinations of tasks involved. The multiple-resource theory (Wickens, 1984) is an attempt to summarize these relationships. They pose a fundamental theoretical dilemma of how to reconcile the complex patterns of multitasking abilities with some notion that the overall capacity of the human system is limited.

In developing EPIC, our theoretical strategy is to make a radical assumption and then explore its consequences through modeling. We assume that all capacity limitations are a result of limited structural resources, rather than a limited cognitive processor. Thus, the EPIC cognitive processor can fire any number of rules simultaneously, but since the peripheral sense organs and effectors are structurally limited, the overall system is sharply limited in capacity. For example, the eyes can only fixate on one place at a time, and the two hands are bottlenecked through a single processor. We also assume that certain apparent limitations in central capacity arise when modality-specific working memories must be used to maintain task information, but we have not yet tested this assumption in the EPIC framework. Thus far, this simple and radical set of assumptions about the nature of multiple-task processing limitations has held up well.

Multiple Tasks and Executive Processes

Some theories of multiple-task performance postulate an executive control process that coordinates the separate multiple tasks (e.g. Norman & Shallice, 1986). We do likewise, but a key feature of our approach is that the executive control process is just another set of production rules. These rules can control other task processes by manipulating information in WM. For example, we assume that each task is represented by a set of production rules that have the task goal appearing in their conditions, and so an executive process rule can suspend a task by removing its governing goal from WM, and then cause it to resume operation by reinserting the goal in WM. Also, the executive process can cause a task to follow a different strategy by placing in WM an item which task rules test for, thus enabling one set of rules, and disabling another. In addition, the executive process may control sensory and motor peripherals directly, such as moving the eye fixation from one point to another, in order to allocate these resources between two tasks. Thus, rather than postulating an executive control mechanism that is somehow different in kind than other cognitive mechanisms, EPIC has a uniform mechanism for the control of behavior, both at the executive level and at the detailed level of individual task actions. As a corollary, learning how to coordinate multiple tasks is simply learning another (possibly difficult) skill, as has been proposed by some recent investigators (Gopher, 1992).

ILLUSTRATION OF EPIC MODELS FOR MULTIPLE TASKS

A Basic Multiple-Task Paradigm

In order to illustrate how EPIC permits us to investigate multiple-task performance in detail, some illustrative results will be presented for one basic, and heavily researched, dual-task situation. In this situation, the subject performs two simple stimulus-response tasks in succession as shown in Figure 2. The two tasks are usually choice reaction tasks, such as pressing one of two keys depending on which of two letters appear, and then making one of two vocal responses depending on whether a high or low frequency tone is heard. The stimuli for the two tasks appear in succession, and the time delay between the two stimuli is manipulated, typically over a range of 0-1000 ms. The subject is typically instructed to give priority to Task 1 (Stimulus 1) over Task 2 by making Response 1 before Response 2, and to make the responses as fast as possible within this constraint. This situation has been extensively studied, and there is an important effect that appears in it, the Psychological Refractory Period (PRP) effect (for thorough reviews, see Bartelson, 1966; Kantowitz, 1974; Pashler, 1990).

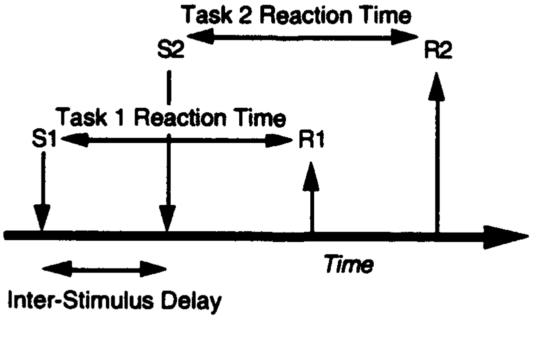

Figure 2. The PRP paradigm. Stimulus 2 is presented with a delay after Stimulus 1, and the time taken to respond to each stimulus is measured.

The PRP effect is that the Task 2 reaction time increases by a substantial amount (hundreds of milliseconds) if Stimulus 2 appears soon after Stimulus 1, and drops to a baseline level if the delay is long enough (see observed curves in Figures 3 and 4). While it is easy to see how this effect would result if the two tasks had to share perceptual or motor processors, the PRP effect occurs even when different stimulus and response modalities are used in the two tasks. In fact, various results show that if the stimuli are in different modalities, the perceptual processing can be done simultaneously for the two tasks (Pashler, 1984).

Demonstration of Parallel Cognitive Processing in Multiple Tasks

The traditional explanation for the PRP effect assumes that the cognitive processor can do only one thing at a time, so the cognitive process of selecting the response for Stimulus 2 must be delayed until Response 1 has been selected or executed. However, results from our quantitative computational model have led us to conclude that response selection can also be done for both tasks simultaneously, meaning that the cognitive processor fires response selection rules in parallel. Here we will present EPIC models for both explanations. In both cases, in order to ensure that the response to Stimulus 1 is always made first, the executive process must delay some aspect of Task 2 until Task 1 is complete. The two explanations differ in which process is postponed: response selection (the traditional explanation) or response production.

We have modeled a data set collected by Hawkins, Rodriguez, and Richer (1979), who conducted one of the most precise and comprehensive PRP studies available. The independent variables included the stimulus and response modalities for the choice reaction tasks and also the difficulty of the second task. Figure 3 shows the observed Task 2 reaction times when the Stimulus 1 is auditory and Response 1 is a left-hand manual button press, and the Stimulus 2 is visual and Response 2 is also a manual button press, but using the right hand.

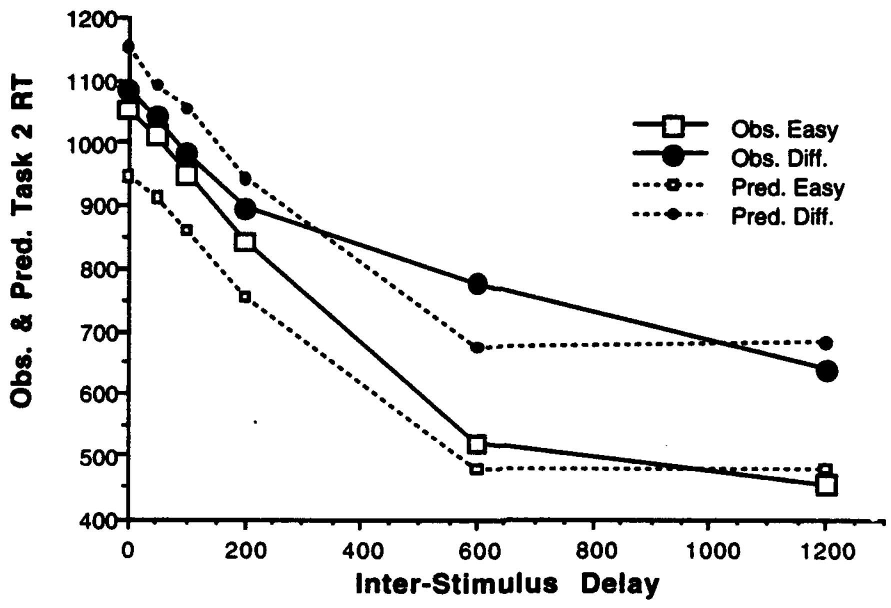

Figure 3. Selection-postponement model: Observed and Predicted Task 2 Reaction Time (RT) for Auditory-Manual Task 1 at two difficulty levels. Easy Task 2 is square points and takes less time than Difficult, shown as circular points. Observed data are large points with solid lines; predicted values are small points with dotted lines.

Considering for the moment just the observed data at long delays, the lower curve is for Task 2 being Easy (a 2-2 stimulus-response mapping); the upper curve is for Task 2 being Difficult (an 8-2 mapping). The Difficult Task 2 takes longer because on the average, more cognitive processor cycles are required to select the response.

Consider first an EPIC model based on the conventional assumption that the cognitive processor can select only one response at a time. The predicted values shown in Figure 3 were obtained with such a *selection-postponement* model. Figure 4 shows a flowchart for the model processing. At the beginning of the trial, the executive process suspends the Task 2 response selection rules by removing the Task 2 goal from WM, and replaces it when the Task 1 response has been made, ensuring that Response 2 will be selected and produced after Response 1. At short delays, Task 2 must wait for the Task 1 response, but at long delays, Task 2 is free to run as soon as Stimulus 2 arrives because Task 1 is complete; thus as shown in Figure 3, the model predicts an overall PRP effect; the Task 2 reaction time is much slower at smaller inter-stimulus delays.

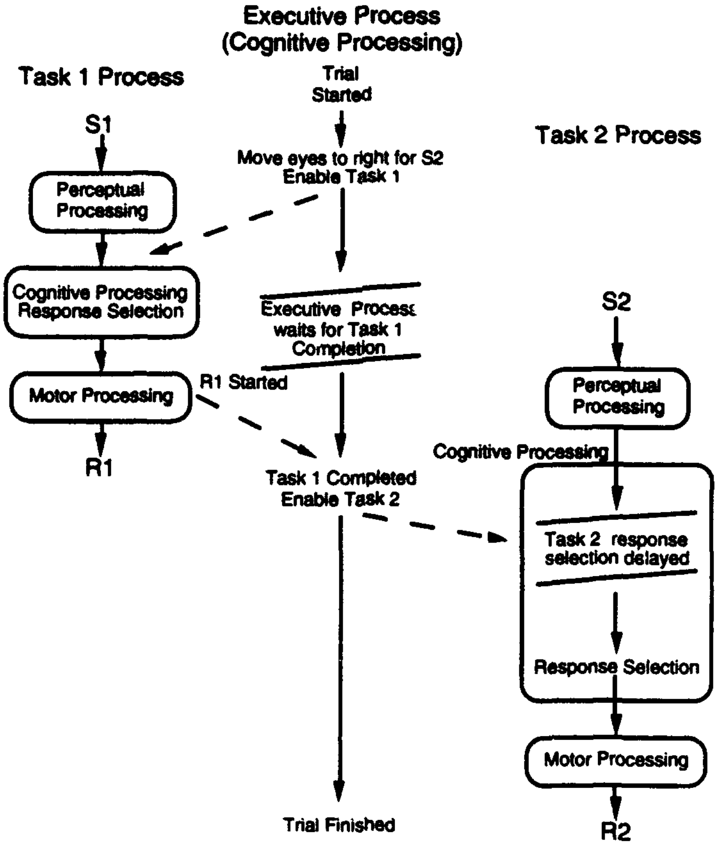

Figure 4. Selection-postponement model: The executive process enables Task 1 response selection processing but does not enable Task 2 response selection until Task 1 is complete.

However, there is a serious misfit in Figure 3. Note how the effect in the data of Task 2 difficulty is much smaller at short delays than at long delays. In contrast, the selection-postponement model predicts that the effect of Task 2 difficulty should be the same at both short and long delays, because Task 2 response selection is always postponed until Task 1 is complete. Such models cannot explain this differential effect of difficulty.

Now consider an EPIC model that takes advantage of the parallel operation of the cognitive processor by postponing response production instead of response selection. The flowchart for this

response-postponement model is shown in Figure 5. The executive process allows Task 2 response selection to go on until a response is selected, but then requires Task 2 to wait for permission to instruct the motor processor to produce the response. After Response 1 has been made, the executive permits Task 2 to send the response information to the motor processor. Figure 6 shows the predicted values for the same data generated by this response-postponement model. Because the Task 2 response selection rules can fire in parallel with the Task 1 rules, the Difficult task does not take much more time than the Easy task at short delays; both perceptual and cognitive processing for the two tasks can be substantially overlapped. However, at long delays there is no overlap, and so the full time for each processor to complete its work shows up in the Task 2 reaction time.

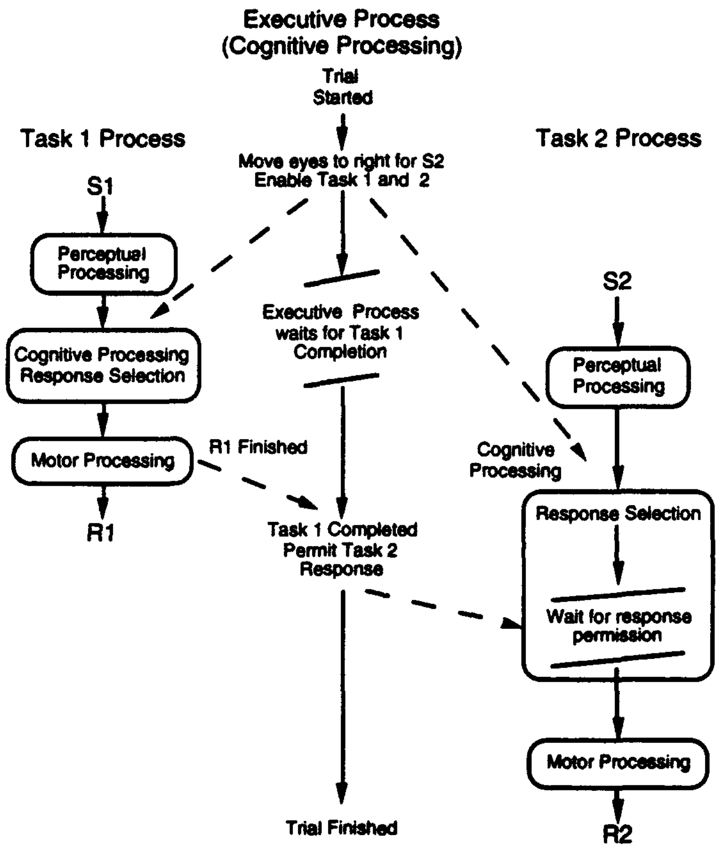

Figure 5. Response-postponement model: The executive process enables response selection processing for both Task 1 and Task 2, but does not allow Task 2 to instruct the motor processor until Task 1 is complete.

The better fits in Figure 6 compared to Figure 3 are also due to two additional mechanisms. First, if Task 1 is complete when Stimulus 2 arrives, then Task 2 can be done in a different mode, in which the response can be sent directly to the motor processor, saving some time. Second, if there is adequate delay between Task 1 and Task 2, the manual motor processor can be preprogrammed with the right-hand feature for Response 2, thereby speeding up the response production. The good fit of this model to the data is typical of our models of PRP data.

To account for the Hawkins *et al.* data set, we propose a different executive process strategy for each of the four combinations of stimulus and response modalities used in the study. Because the subjects were very well practiced, it seems reasonable that the executive strategies will minimize response time as much as possible, and the executive strategies thus depend on the modality combination. For example, if both stimuli are visual, the executive process moves the eye from the

site of the first stimulus when it is detected to the second stimulus, while allowing both tasks to run to completion as soon as they receive their input without postponement or other overhead. This is optimal because the eye movement delay is long enough to ensure that the responses appear in the correct order. The resulting set of four executive models, running with identical rule sets for the two tasks, accounts for almost all of the systematic variance among the mean Task 2 reaction times across inter-stimulus delays, stimulus modalities, and response modalities, having $r^2 = .99$, $N = 48$ (see Meyer & Kieras (1994), for a discussion of the details of these results and the issues of goodness-of-fit and degrees of freedom).

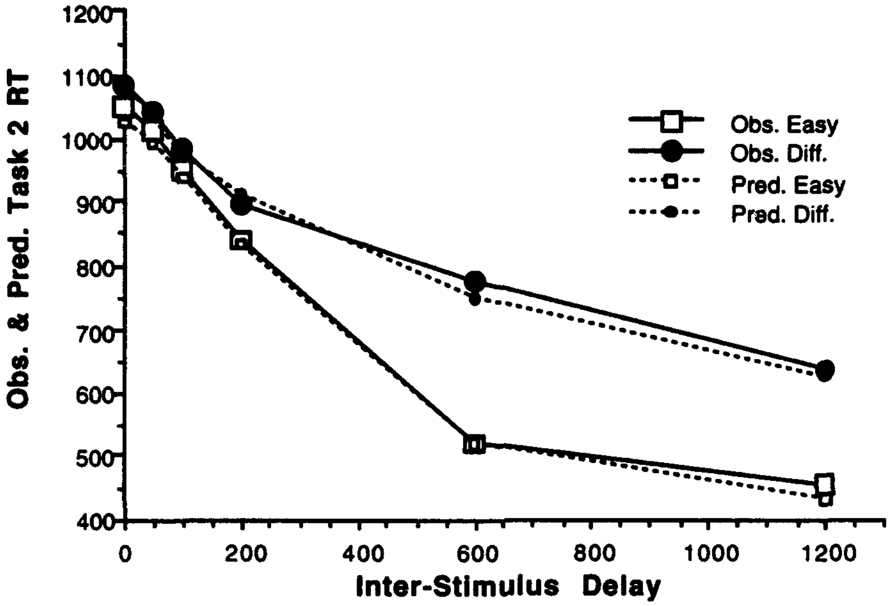

Figure 6. Response-postponement model: Observed and Predicted Task 2 Reaction Time (RT) for Auditory-Manual Task 1 at two difficulty levels. Easy Task 2 is square points and takes less time than Difficult, shown as circular points. Observed data are large points with solid lines; predicted values are small points with dotted lines. The model postpones response production

Current Work on a Classic Multiple-Task Paradigm

Another model under development concerns a very heavily studied multiple-task paradigm in which the subject must perform both a tracking task and a choice task. Developing an EPIC model for tracking brings out many key issues about the nature of tracking; our approach has been to represent tracking as a distinct motor processor "style" in which the human has a well-learned skill for operator the tracking control; the cognitive processor need only supervise the process. Our current work is modeling some results obtained by Martin-Emerson and Wickens(1992) which are especially revealing about the role of eye movements and the use of visual information during such a dual task.

APPLICATION OF EPIC TO HUMAN-COMPUTER INTERACTION

Comparison to Other Models of Human-Computer Interaction

Since it is a general model of human information processing and performance, EPIC should be applicable to many issues in human-computer interaction (HCI). In fact it incorporates and extends some of the most successful theoretical concepts in HCI.

Production-rule models, and their higher-level relative, GOMS models (Card, Moran, & Newell, 1983; Kieras, 1988), appear to capture the procedural requirements of an interface very well. In the Cognitive Complexity Theory (CCT) approach (Kieras & Polson, 1985; Bovair, Kieras, & Polson, 1990), the production rules are organized in a GOMS format, being organized hierarchically and sequentially by goals and methods. But models at the level of the MHP appear to capture very well the processing sequence characteristics of a task. For example, the scheduling-chart models in Gray, John, and Atwood (1992) for telephone operator tasks show which processor runs at what time, and which waits for output from another. This seems to be a useful characterization for tasks such as telephone operator tasks, because the sequence of processing would be optimized for speed and stable for such well-practiced, time-critical tasks. Since both CCT and MHP models seem to be successful in their domains, it is important to see how they both fit into a framework such as EPIC.

The CCT production-rule models can be mapped to the EPIC architecture in that the CCT model production rules are simply executed as-is by the cognitive processor. The perceptual and motor operators "bypassed" in the CCT analysis would be lower-level methods that interact closely with the perceptual and motor processors, as would be involved, for example, in visually locating an object on the screen. If the quality of the interface depends heavily on such perceptual-motor interactions, then an EPIC model should be more exact and useful than a CCT model.

The Gray et al. scheduling-chart models for the telephone operator tasks relate to EPIC in that they show the sequence and relations of the processor activities, but the method followed by the human in doing the task is implicit, rather than explicit, in the schedule chart. So analyzing one of these tasks with EPIC requires writing the production rules to be followed by the cognitive processor in performing the task, ensuring for example, that eye movements are made at the proper time. Such a model can then generate behavioral predictions for any instance of the task. The explicit production-rule representation also facilitates comparison of the structure of different tasks.

A High-Performance Human-Computer Interaction Task

We are developing EPIC models for the telephone operator tasks studied by Gray, John, and Atwood (1992). These tasks are of special interest because an analysis of them in terms of the MHP was of considerable economic value in this domain where a second's difference in average task completion time is worth a substantial amount of money. The EPIC architecture is "programmed" with a set of production rules capable of performing all possible instances of the telephone operator tasks that are within the scope of the rules. The perceptual and motor processors generate the times required to move the eyes around, perceive stimuli on the operator's workstation screen, and reach for and strike keys under the direction of the cognitive processor rules. These rules can arrange to overlap some of the activities in order to save time. These EPIC models for the telephone operator tasks are similar to our PRP task executive models, in that they are optimized for speed by overlapping as many processes as possible, and by preparing or executing motor movements as soon as the task permits. Such optimized rules are organized according to the optimal temporal interleaving of the peripheral processes, analogous in organization to highly speed-optimized code for a real-time computer system.

In preliminary results, the EPIC models appear capable of generating usefully accurate predicted completion time for such tasks rather more easily and generally than the MHP-based analyses. This

work has been presented in Wood, Kieras, and Meyer (1994).

Representation of Skill in HCI Tasks

In high-performance tasks such as the telephone operator tasks, and indeed many multiple-task situations, it is critical for the human operator to act as rapidly as possible. Constructing models for such tasks in EPIC allows us to explore how such procedural skill would be represented, and how it might develop. Based on existing research, representing procedural knowledge as structured in terms of a hierarchy of goals and methods, as in the GOMS model, appears to be both theoretical appealing and empirical accurate, at least in many task domains such as text editing. Such a representation is analogous to well-modularized code in the structured programming style. Furthermore, if the interface can be operated with a simple and consistent set of methods, then it is relatively fast to learn. Thus procedures that are well-structured in GOMS terms should correspond to easily learned interfaces.

However, a disadvantage of such GOMS-structured procedural knowledge is that, as represented in EPIC, there is a certain amount of overhead in processing the hierarchically structured procedural knowledge, analogous to the subroutine calling overhead in computer programs. Thus GOMS-structured procedures may be inherently slower than less well-structured representations.

But there is an additional speed disadvantage of GOMS-structured methods: they are committed to executing only in the context of accomplishing the current goal. In contrast, our EPIC models can, when appropriate, take advantage of certain possibilities for speeding up execution that involve making actions early, and out of their apparent procedural context, such as starting an eye movement during one part of the task in anticipation of getting information needed in a later part of the task. Such anticipatory actions are not contained strictly in the goal-based methods to which they are relevant. This approach to organizing actions violates a principle of modularization in good computer programming practice, in which the computations relevant to particular programming goal are kept together, encapsulated in their own distinct routines. Thus the greater speed is had at the expense of the modular goal-organized procedures.

Yet EPIC is not rigidly committed to either GOMS-structured production rules, or speed-optimized production rules. Rather, using EPIC brings out the important puzzle of when the production rules in a model would be GOMS-structured versus optimized for speed. Perhaps the production rules for time-stressed highly practiced skills would be in the speed-optimized form, while normal, less-practiced skills would be GOMS-structured. Learning a procedural skill might progress from the initial stages to a fully automated, or "tuned" state by changes in the production-rule organization (see Anderson, 1987; Card, Moran, & Newell, 1983; Schneider, 1985). When the system is first learned, a GOMS representation of the skill seems reasonable, in that the user's procedural knowledge is organized in terms of methods for accomplishing goals, and these methods are executed in a sequential hierarchical fashion, especially if speed is not critical or the perceptual and motor activities must be done sequentially. These methods could be refined to some extent with further practice (Bovair, Kieras, & Polson, 1990). But after extreme practice, especially if speed of operation is critical and perceptual and motor activities can be done simultaneously, the methods may become "flattened" and interleaved, so the original goal-hierarchical sequential form is lost in favor of a representation that permits the fastest possible temporal coordination of the processes with minimal cognitive activity.

The interesting question this analysis brings out concerns the extent to which there is some form of tradeoff between whether an interface would be easily learned by virtue of having a good GOMS structure versus it being easily speed-optimized by virtue of having a structure that permits time-consuming actions to be interleaved and overlapped. If we understood the relationship between well-modularized and speed-optimized procedures, we could determine whether an interface design can support an extreme level of skill by determining whether it would be possible for speed-optimized procedures to be derived from the initial GOMS-structured procedures. For example, compared to a system that will always be operated according to sequential methods for hierarchical goals, a system

that must eventually be operated at very high speed will not only have to meet more stringent requirements on display design and input devices, it might also require very specific sequences of display events and input operations. For example, one of the workstations analyzed in Gray, John, and Atwood (1992) was unnecessarily slow because one input operation could not be overlapped with other processes.

CONCLUSION

The PRP and HCI models summarized here illustrate how the EPIC framework can represent a task situation in quantitative detail, and can address some fundamental issues about the cognitive architecture and how multiple tasks are coordinated. One result is that a central bottleneck is not a necessary assumption, and that data thought to require such an assumption can be explained by more obvious competition for the same peripherals in the context of the requirements of the task. The role of the executive process as a coordinator and sequencer of task performance is made clear. The executive strategies attempt to optimize the task performance by sequencing the activities of the peripheral processors based on their temporal characteristics.

The potential for EPIC to function as an engineering model in practical domains such as computer user interface design is clear from our current work with telephone operator tasks. In addition, by developing and applying an explicit theoretical framework, it is possible to explore otherwise unrealized and intractable theoretical issues. For example, our current work on tracking tasks has brought out many poorly understood aspects of the tracking task. Another insight comes from the above discussion about the representation of skill, which points to a hitherto unrealized twist on the ease-of-learning/speed-of-use distinction and the relation between interfaces for desktop and office tasks and those for supporting high-performance tasks.

REFERENCES

Anderson, J. R. (1976). *Language, memory, and thought*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Anderson, J. R. (1987). Skill acquisition: Compilation of weak-method problem solutions. *Psychological Review,* **94**, 192-210.

Bartelson, P. (1966). Central intermittency 20 years later. *Quarterly Journal of Experimental Psychology*, **18**, 153-164.

Bovair, S., Kieras, D. E., & Polson, P. G. (1990). The acquisition and performance of text editing skill: A cognitive complexity analysis. *Human-Computer Interaction,* **5**, 1-48.

Card, S. K., Moran, T. P., & Newell, A. (1983). *The psychology of human-computer interaction*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Gray, W. D., John, B. E., & Atwood, M. (1992). The precis of Project Ernestine, or an overview of a validation of GOMS. In P. Bauersfeld, J. Bennett, and G. Lynch (Eds.), *CHI'92 Conference Proceedings*, ACM, New York.

Gopher, D. (1992). Attentional control: Acquisition and execution of attentional strategies. In D. E.. Meyer & S. Kornblum (Eds.), *Attention and performance XIV: A silver jubilee*. Hillsdale, NJ: Erlbaum.

Gopher, D., & Donchin, E. (1986). Workload: An examination of the concept. In K.R. Boff et al. (Eds.), *Handbook of perception and performance*, Vol. II (pp. 41.1-41.49). New York: Wiley.

Hawkins, H. L, Rodriguez, E., & Richer, G. (1979). Is time-sharing a general ability? Technical Report No. 3, Center for Cognitive and Perceptual Research, University of Oregon.

Kantowitz, B. H.. (1974). Double stimulation. In B. H. Kantowitz (Ed.), *Human information processing: Tutorials in performance and cognition* . Hillsdale, NJ: Lawrence Erlbaum Associates.

Kieras, D. E. (1988). Towards a practical GOMS model methodology for user interface design. In M. Helander (Ed.), *Handbook of Human–Computer Interaction* (pp. 135–158). Amsterdam: North–Holland Elsevier.

Kieras, D. E. (1990). The role of cognitive simulation models in the development of advanced training and testing systems. In N. Frederiksen, R. Glaser, A. Lesgold, & M. Shafto (Eds.), *Diagnostic monitoring of skill and knowledge acquisition* . Hillsdale, NJ: Erlbaum.

Kristofferson, A. B. (1967). Attention and psychophysical time. In A. F. Sanders (Ed.), *Attention and performance* (pp. 93-100). Amsterdam: North-Holland Publishing Co.

Martin-Emerson, R., & Wickens, C.D. (1992). The vertical visual field and implications for the head-up display. *Proceedings of the 36th Annual Symposium of the Human Factors Society.* Santa Monica, CA: Human Factors Society.

McLeod, P. D. (1977). A dual task response modality effect: Support for multiprocessor models of attention. *Quarterly Journal of Experimental Psychology* , **29**, 651-668.

Meyer, D. E., & Kieras, D. E. (1992). The PRP effect: Central bottleneck, perceptual-motor limitations, or task strategies? Paper presented at the meeting of the Psychonomics Society, St. Louis, MO, November.

Meyer, D. E., & Kieras, D. E. (1994). Computational modeling of basic multiple-task performance: The EPIC architecture and psychological refractory period phenomena. Manuscript in preparation.

Norman, D. A., & Shallice, T. (1986). Attention to action: Willed and automatic control of behavior. In R.J. Davidson et al. (Eds.), *Consciousness and self-regulation* , Vol. 4. New York, Plenum Press.

Pashler, H. (1984). Processing stages in overlapping tasks: Evidence for a central bottleneck. *Journal of Experimental Psychology: Human Perception and Performance* , **10**, 358-377.

Pashler, H. (1990). Do response modality effects support multiprocessor models of divided attention? *Journal of Experimental Psychology: Human Perception and Performance* , **10**, 826-842.

Peck, V. A., & John, B. E. (1992). Browser-SOAR: A computational model of a highly interactive task. In P. Bauersfeld, J. Bennett, and G. Lynch (Eds.), *CHI'92 Conference Proceedings* , ACM, New York.

Rosenbaum, D.A. (1980). Human movement initiation: Specification of arm, direction, and extent. *Journal of Experimental Psychology: General* , **109** , 475-495.

Schneider, W. (1985). Training high-performance skills. *Human Factors* , **27**, 285-300.

Welford, A.T. (1952). The "psychological refractory period" and the timing of high speed performance - A review and a theory. *British Journal of Psychology,* **43**, 2-19.

Wickens, C.D. (1984). *Engineering psychology and human performance* . Columbus, OH: Charles F. Merrill.

Wood, S., Kieras, D., & Meyer, D. (1994). An EPIC model for a high-performance task. Poster presented at CHI'94 ACM Conference on Human Factors in Computing, Boston, April 25-28.

Dr. Beth Adelson
Department of Psychology
Rutgers University
Camden, NJ 08102

Technical Document Center
AL/HGR-TDC
Wright-Patterson AFB
OH 45433-6503

Dr. David L. Alderton, Code 131
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. James A. Anderson
Department of Cognitive and
Linguistic Sciences
Brown University
Box 1978
Providence, RI 02912

Dr. John R. Anderson
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. Stephen J. Andriole, Chairman
College of Information Studies
Drexel University
Philadelphia, PA 19104

Dr. Gregory Anrig
Educational Testing Service
Princeton, NJ 08541

Technical Director, ARI
5001 Eisenhower Avenue
Alexandria, VA 22333

Edward Atkins
13705 Lakewood Ct.
Rockville, MD 20850

Dr. Michael E. Atwood
NYNEX
AI Laboratory
500 Westchester Avenue
White Plains, NY 10604

Dr. Patricia Baggett
School of Education
610 E. University, Rm 1302D
University of Michigan
Ann Arbor, MI 48109-1259

Dr. Meryl S. Baker
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Pierre Baldi
Division of Biology, 216-76
California Institute of Technology
Pasadena, CA 91125

Dr. William O. Berry
Director of Life and
Environmental Sciences
AFOSR/NL, N1, Bldg. 410
Bolling AFB, DC 20332-6448

Dr. Menucha Birenbaum
Educational Testing
Service
Princeton, NJ 08541

Dr. C. Alan Boneau
Department of Psychology
George Mason University
4400 University Drive
Fairfax, VA 22030

Dr. J. C. Boudreaux
Manufacturing Engineering Lab
National Institute of
Standards and Technology
Gaithersburg, MD 20899

Dr. Gordon H. Bower
Department of Psychology
Stanford University
Stanford, CA 94305

Dr. Robert Breaux
Code 252
Naval Training Systems Center
Orlando, FL 32826-3224

Dr. Ann Brown
Graduate School of Education
University of California
EMST-4533 Tolman Hall
Berkeley, CA 94720

CDR Robert Carter
HCI Laboratory
Naval Research Laboratory
Washington, DC 20375

Dr. Eduardo Cascallar
Educational Testing Service
Rosedale Road
Princeton, NJ 08541

Dr. Paul R. Chatelier
Perceptronics
1911 North Ft. Myer Dr.
Suite 800
Arlington, VA 22209

Dr. Michelene Chi
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15260

Dr. Susan Chipman
Cognitive Science Program
Office of Naval Research
800 North Quincy St.
Arlington, VA 22217-5000

Dr. Raymond E. Christal
UES LAMP Science Advisor
AL/HRMIL
Brooks AFB, TX 78235

Dr. David E. Clement
Department of Psychology
University of South Carolina
Columbia, SC 29208

Dr. Rodney Cocking
NIMH, Basic Behavior and
Cognitive Science Research
5600 Fishers Lane, Rm 11C-10
Parklawn Building
Rockville, MD 20857

Director, Life Sciences
Office of Naval Research
Code 114
Arlington, VA 22217-5000

Director, Cognitive and
Neural Sciences, Code 1142
Office of Naval Research
Arlington, VA 22217-5000

Director
Training Systems Department
Code 15A
Navy Personnel R&D Center
San Diego, CA 92152-6800

Library, Code 231
Navy Personnel R&D Center
San Diego, CA 92152-5800

Commanding Officer
Naval Research Laboratory
Code 4827
Washington, DC 20375-5000

Dr. Albert T. Corbett
Department of Psychology
Carnegie-Mellon University
Pittsburgh, PA 15213

Dr. Michael Cowen
Code 142
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Kenneth B. Cross
Anacapa Sciences, Inc.
P.O. Box 519
Santa Barbara, CA 93102

Dr. Peter Culicover
Director, Center for Cognitive
Science
208 Ohio Stadium East
1961 Tuttle Park Place
Columbus, OH 43210-1102

Dr. Diane Damos
Dept. of Human Factors
Institute of Safety &
Systems Management
Univ. of Southern California
Los Angeles, CA 90089-0021

Margaret Day, Librarian
Applied Science Associates
P.O. Box 1072
Butler, PA 16003

Dr. Geory Delacote
Exploratorium
3601 Lyon Street
San Francisco, CA
94123

Dr. Sharon Derry
Florida State University
Department of Psychology
Tallahassee, FL 32306

Dr. Stephanie Doane
University of Illinois
Department of Psychology
603 East Daniel Street
Champaign, IL 61820

Dr. Emanuel Donchin
University of Illinois
Department of Psychology
603 East Daniel Street
Champaign, IL 61820

Defense Technical
Information Center
DTIC/DDA-2
Cameron Station, Bldg 5
Alexandria, VA 22314
(4 Copies)

Dr. Richard Duran
Graduate School of Education
University of California
Santa Barbara, CA 93106

Dr. John Ellis
Navy Personnel R&D Center
Code 15
San Diego, CA 92152-6800

Dr. Susan Epstein
144 S. Mountain Avenue
Montclair, NJ 07042

ERIC Facility-Acquisitions
1301 Piccard Drive, Suite 300
Rockville, MD 20850-4305

Dr. K. Anders Ericsson
University of Colorado
Department of Psychology
Campus Box 345
Boulder, CO 80309-0345

Dr. Martha Evens
Dept. of Computer Science
Illinois Institute of Technology
10 West 31st Street
Chicago, IL 60616

Dr. Beatrice J. Farr
Army Research Institute

PERI-IC
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Marshall J. Farr
Farr-Sight Co.
2520 North Vernon Street
Arlington, VA 22207

Dr. Kathleen Fernandes
Naval Ocean Systems Center
Code 423
San Diego, CA 92152

Mr. Wallace Feurzeig
Educational Technology
Bolt Beranek & Newman
10 Moulton St.
Cambridge, MA 02238

Dr. Victor Fields
Department of Psychology
Montgomery College
Rockville, MD 20850

Dr. J. D. Fletcher
Institute for Defense Analyses
1801 N. Beauregard St.
Alexandria, VA 22311

Dr. Lawrence T. Frase
Executive Director
Division of Cognitive and
Instructional Science
Educational Testing Service
Princeton, NJ 08541

Dr. Carl H. Frederiksen
Dept. of Educational Psychology
McGill University
3700 McTavish Street
Montreal, Quebec
CANADA H3A 1Y2

Dr. Norman Frederiksen
Educational Testing Service
(05-R)
Princeton, NJ 08541

Dr. Alfred R. Fregly
AFOSR/NL, Bldg. 410
Bolling AFB, DC 20332-6448

Dr. Alinda Friedman
Department of Psychology
University of Alberta
Edmonton, Alberta
CANADA T6G 2E9

Dr. Jack J. Gelfand
Department of Psychology
Princeton University
Princeton, NJ 08544-1010

Dr. Dedre Gentner
Northwestern University
Department of Psychology
2029 Sheridan Road
Swift Hall, Rm 102
Evanston, IL 60208-2710

Chair, Department of
Computer Science
George Mason University
Fairfax, VA 22030

Dr. Helen Gigley
Naval Research Lab., Code 5530
4555 Overlook Avenue, S. W.
Washington, DC 20375-5000

Dr. Philip Gillis
ARI-Fort Gordon
ATTN: PERI-ICD
Fort Gordon, GA 30905

Mr. Lee Gladwin
305 Davis Avenue
Leesburg, VA 22075

Dr. Robert Glaser
Learning Research
& Development Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15260

Dr. Marvin D. Glock
101 Homestead Terrace
Ithaca, NY 14856

Dr. Sam Glucksberg
Department of Psychology
Princeton University
Princeton, NJ 08544-1010

Dr. Susan R. Goldman
Peabody College, Box 45
Vanderbilt University
Nashville, TN 37203

Dr. Sherrie Gott
AFHRL/MOMJ
Brooks AFB, TX 78235-5601

Dr. Arthur C. Graesser
Department of Psychology
Memphis State University
Memphis, TN 38152

Dr. Wayne Gray
Graduate School of Education
Fordham University
113 West 60th Street
New York, NY 10023

Dr. James G. Greeno
School of Education
Stanford University
Room 311
Stanford, CA 94305

Dr. Stephen Grossberg
Center for Adaptive Systems
Room 244
111 Cummington Street
Boston University
Boston, MA 02215

Dr. Michael Habon
DORNIER GMBH
P.O. Box 1420
D-7990 Friedrichshafen 1
WEST GERMANY

Marilyn Halpern, Librarian
Brigham Library
Educational Testing Service
Carter and Rosedale Roads
Princeton, NJ 08541

Dr. Kristian J. Hammond
Department of Computer Science
University of Chicago
1100 E. 58th St.
Chicago, IL 60637

Dr. Stephen J. Hanson
Learning & Knowledge
Acquisition Research
Siemens Research Center
755 College Road East
Princeton, NJ 08540

Dr. Patrick R. Harrison
Computer Science Department
U.S. Naval Academy
Annapolis, MD 21402-5002

Dr. Keith Holyoak
Department of Psychology
University of California
Los Angeles, CA 90024

Ms. Julia S. Hough
Cambridge University Press
40 West 20th Street
New York, NY 10011

Dr. William Howell
Chief Scientist
AFHRL/CA
Brooks AFB, TX 78235-5601

Dr. Earl Hunt
Dept. of Psychology, NI-25
University of Washington
Seattle, WA 98195

Dr. Jack Hunter
2122 Coolidge Street
Lansing, MI 48906

Dr. Martin J. Ippel
Center for the Study of
Education and Instruction
Leiden University
P. O. Box 9555
2300 RB Leiden
THE NETHERLANDS

Z. Jacobson
Bureau of Management Consulting
701-365 Laurier Ave., W.
Ottawa, Ontario K1H 5W3
CANADA

Dr. Robert Jannarone
Elec. and Computer Eng. Dept.
University of South Carolina
Columbia, SC 29208

Dr. Claude Janvier
CIRADE, X-7120
UQAM
P. O. Box 8888, Succ. A
Montreal, Quebec H3C 3P8
CANADA

Dr. Robin Jeffries
Hewlett-Packard
Laboratories, 1U-17
P.O. Box 10490
Palo Alto, CA 94303-0969

Dr. Edgar M. Johnson
Technical Director
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333-5600

Dr. Michael Kaplan
Office of Basic Research
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333-5600

Dr. Milton S. Katz
PSC 802 Box 15
FPO AE 09499-1500

Dr. Wendy Kellogg
IBM T. J. Watson
Research Ctr.
P.O. Box 704
Yorktown Heights, NY 10598

Dr. J.A.S. Kelso
Center for Complex Systems
Building MT 9
Florida Atlantic University
Boca Raton, FL 33431

Dr. David Kieras
Technical Communication Program
TIDAL Bldg., 2360 Bonisteel Blvd.
University of Michigan
Ann Arbor, MI 48109-2108

Dr. Sung-Ho Kim
Educational Testing Service

Princeton, NJ 08541

Dr. Sylvan Kornblum
University of Michigan
Mental Health Research Institute
205 Washtenaw Place
Ann Arbor, MI 48109

Dr. Richard J. Koubek
School of Industrial
Engineering
Grissom Hall
Purdue University
West Lafayette, IN 47907

Dr. Benjamin Kuipers
University of Texas at Austin
Department of Computer Sciences
Austin, Texas 78712

Dr. Patrick Kyllonen
AFHRL/MOEL
Brooks AFB, TX 78235

Dr. Anita Lancaster
Assistant Director
Defense Manpower Data Center
Fourth Floor
1600 Wilson Blvd.
Arlington, VA 22209

Dr. Pat Langley
AI Research Branch
Mail Stop 244-17
NASA Ames Research Ctr.
Moffett Field, CA 94035

Richard Lanterman
Commandant (G-PWP)
US Coast Guard
2100 Second St., SW
Washington, DC 20593-0001

Dr. Robert W. Lawler
Matthews 118
Purdue University
West Lafayette, IN 47907

Dr. Paul E. Lehner
Department of Information
Systems & Engineering
George Mason University
4400 University Drive
Fairfax, VA 22030-4444

Dr. Alan M. Lesgold
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr. Richard Lesh
Educational Testing Service
Princeton, NJ 08541

Dr. Michael Levine
Educational Psychology
210 Education Bldg.
1310 South Sixth Street
University of IL at
Urbana-Champaign
Champaign, IL 61820-6990

Dr. Marcia C. Linn
Graduate School
of Education, EMST
Tolman Hall
University of California
Berkeley, CA 94720

Dr. William L. Maloy
Code 04
NETPMSA
Pensacola, FL 32509-5000

Dr. Evans Mandes
George Mason University
4400 University Drive
Fairfax, VA 22030

Dr. Sandra P. Marshall
Dept. of Psychology
San Diego State University
San Diego, CA 92182

Dr. Clessen J. Martin
Head, DoD Coordinator,
Recruiting Plans and Programs
Branch Code: PERS 2FF/234
Navy Annex, Room 2832
Washington, DC 20350

Dr. Elizabeth Martin
AL/HRA, Stop 44
Williams AFB
AZ 85240

Dr. John Mayer
Technical Communications
Program
2360 Bonisteel Blvd.
University of Michigan
Ann Arbor, MI 48109

Dr. Richard E. Mayer
Department of Psychology
University of California
Santa Barbara, CA 93106

Dr. Kathleen McKeown
Columbia University
Department of Computer Science
450 Computer Science Building
New York, NY 10027

Dr. Joseph McLachlan
Navy Personnel Research
and Development Center
Code 14
San Diego, CA 92152-6800

Dr. Michael McNeese
DET-1, AL/CFHI
BLDG 248
Wright-Patterson AFB, OH 45432

Dr. Alan Meyrowitz
Naval Research Laboratory
Code 5510
4555 Overlook Ave., SW
Washington, DC 20375-5000

Dr. Ryszard S. Michalski
Center for Artificial Intelligence
George Mason University
Science and Tech II, Rm.411
4400 University Drive
Fairfax, VA 22030-4444

Dr. Andrew R. Molnar
Applications of Advanced
Technologies, Rm. 635
National Science Foundation
Washington, DC 20550

Dr. Randy Mumaw
Human Sciences
Westinghouse Science
& Technology Ctr.
1310 Beulah Road
Pittsburgh, PA 15235

Dr. Allen Munro
Behavioral Technology
Laboratories - USC
250 N. Harbor Dr., Suite 309
Redondo Beach, CA 90277

Distribution Support Division
Bureau of Naval Personnel
PERS-471D
Washington, DC 20370

Academic Progs. & Research Branch
Naval Technical Training Command
Code N-62
NAS Memphis (75)
Millington, TN 38054

Mr. J. Nelissen
Twente University
Fac. Bibl. Toegepaste Onderwyskunde
P. O. Box 217
7500 AE Enschede
The NETHERLANDS

Dr. Donald A. Norman
Department of Cognitive Science
University of California
La Jolla, CA 92093-0515

Director
Training Systems Department
NPRDC (Code 14)
San Diego, CA 92152-6800

Library, NPRDC
Code 041
San Diego, CA 92152-6800

Librarian
Naval Center for Applied Research
in Artificial Intelligence
Naval Research Laboratory
Code 5510
Washington, DC 20375-5000

Dr. Stellan Ohlsson
Learning R & D Center
University of Pittsburgh
Pittsburgh, PA 15260

Mathematics Division
Office of Naval Research
Code 1111
800 North Quincy Street
Arlington, VA 22217-5000

Office of Naval Research,
Code 1142CS
800 N. Quincy Street
Arlington, VA 22217-5000
(6 Copies)

Assistant for Training Technology
and Human Factors
Office of the DCNO(MPT) (Op-11E)
Department of the Navy
Washington, DC 20350-2000

Special Assistant for Research
Management
Chief of Naval Personnel (PERS-OUT)
Department of the Navy
Washington, DC 20350-2000

Dr. Judith Orasanu
Mail Stop 239-1
NASA Ames Research Center
Moffett Field, CA 94035

Dr. Jesse Orlansky
Institute for Defense Analyses
1801 N. Beauregard St.
Alexandria, VA 22311

Dr. Okchoon Park
Army Research Institute
PERI-2
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Roy Pea
Institute for the
Learning Sciences
Northwestern University
1890 Maple Avenue
Evanston, IL 60201

Dr. Ray S. Perez
ARI (PERI-II)

5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Nancy N. Perry
Naval Education and Training
Program Support Activity
Code-047
Building 2435
Pensacola, FL 32509-5000

CDR Frank C. Petho
Naval Postgraduate
School
Code OR/PE
Monterey, CA 93943

Dept. of Administrative Sciences
Code 54
Naval Postgraduate School
Monterey, CA 93943-5026

Dr. Elizabeth A. Phelps
Department of Psychology
New School for Social Research
65 Fifth Avenue
New York, NY 10003

Dr. Peter Pirolli
School of Education
University of California
Berkeley, CA 94720

Dr. Martha Polson
Department of Psychology
University of Colorado
Boulder, CO 80309-0344

Dr. Peter Polson
University of Colorado
Department of Psychology
Boulder, CO 80309-0344

Dr. Joseph Psotka
ATTN: PERI-IC
Army Research Institute
5001 Eisenhower Ave.
Alexandria, VA 22333-5600

Psyc Info - CD and M
American Psychological Assoc.
1200 Uhle Street
Arlington, VA 22201

Mr. Paul S. Rau
Code U-33
Naval Surface Warfare Center
White Oak Laboratory
Silver Spring, MD 20903

Dr. J. Wesley Regian
AFHRL/IDI
Brooks AFB, TX 78235

Dr. Fred Reif
CDEC, Smith Hall
Carnegie-Mellon University
Pittsburgh, PA 15213

Dr. Charles M. Reigeluth
Chairman, Instructional
Systems Technology
School of Education, Rm. 210
Indiana University
Bloomington, IN 47405

Dr. Daniel Reisberg
Reed College
Department of Psychology
Portland, OR 97202

Dr. Brian Reiser
Institute for the Learning Sciences
Northwestern University
1890 Maple Avenue
Evanston, IL 60201-3142

Dr. Lauren Resnick
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Mr. W. A. Rizzo
Head, Human Factors Division
Naval Training Systems Center
Code 26
12350 Research Parkway
Orlando, FL 32826-3224

Dr. Linda G. Roberts
Science, Education, and
Transportation Program
Office of Technology Assessment
Congress of the United States
Washington, DC 20510

Dr. Andrew M. Rose
American Institutes
for Research
3333 K Street, N.W.
Washington, DC 20007

Dr. Eduardo Salas
Human Factors Division (Code 262)
12350 Research Parkway
Naval Training Systems Center
Orlando, FL 32826-3224

Dr. Mark Schlager
SRI International
333 Ravenswood Ave.
Room BS-131
Menlo Park, CA 94025

Dr. Walter Schneider
Learning R&D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15260

Dr. Alan H. Schoenfeld
University of California
Department of Education
Berkeley, CA 94720

Dr. Mary Schratz
4100 Parkside
Carlsbad, CA 92008

Dr. Judith W. Segal
OERI
555 New Jersey Ave., NW
Washington, DC 20208-5648

Dr. Robert J. Seidel
US Army Research Institute
5001 Eisenhower Ave.
Alexandria, VA 22333

Dr. Colleen M. Seifert
Department of Psychology
University of Michigan
330 Packard Road
Ann Arbor, MI 48104

Dr. Terrence J. Sejnowski
Professor
The Salk Institute
P. O. Box 85800
San Diego, CA 92138-9216

Dr. Michael G. Shafto
NASA Ames Research Ctr.
Mail Stop 262-1
Moffett Field, CA 94035-1000

Mr. Richard J. Shavelson
Graduate School of Education
University of California
Santa Barbara, CA 93106

Dr. Jerome E. Singer
Department of Medical Psychology
Uniformed Services Univ. of the
Health Sciences
4301 Jones Bridge Road
Bethesda, MD 20814-4799

Dr. Jan Sinnott
Department of
Computer Science
Towson State University
Towson, MD 21204

Dr. Derek Sleeman
Computing Science Department
The University
Aberdeen AB9 2FX
Scotland
UNITED KINGDOM

Dr. Robert Smillie
Naval Ocean Systems Center
Code 443
San Diego, CA 92152-5000

Dr. Richard E. Snow
School of Education
Stanford University
Stanford, CA 94305

Dr. Kathryn T. Spoehr
Department of Cognitive
& Linguistic Sciences
Box 1978
Brown University
Providence, RI 02912

Dr. James J. Staszewski
Dept. of Psychology
University of South Carolina
Columbia, SC 29210

Dean, College of Behavioral
and Social Sciences
University of Maryland,
Baltimore County
Baltimore, MD 21228

Dr. Kurt VanLehn
Learning Research
& Development Ctr.
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15260

Dr. Jerry Vogt
Department of Psychology
St. Norbert College
De Pere, WI 54115-2099

Dr. Douglas Wetzel
Code 15
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Barbara White
School of Education
Tolman Hall, EMST
University of California
Berkeley, CA 94720

Alexandra K. Wigdor
NRC MH-176
2101 Constitution Ave.
Washington, DC 20418

Dr. David Wiley
School of Education
and Social Policy
Northwestern University
Evanston, IL 60208

Dr. David C. Wilkins
University of Illinois
Department of Computer Science
405 North Mathews Avenue
Urbana, IL 61801

Dr. Bruce Williams
Department of Educational
Psychology
University of Illinois
Urbana, IL 61801

Dr. Kent E. Williams
Virginia Polytechnic Institute
and State University

[illegible]

Department of Industrial and
Systems Engineering/MSL
1900 Kraft Drive
Blacksburg, VA 24060

Dr. Robert A. Wisher
U.S. Army Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333-5600

Dr. Merlin C. Wittrock
Graduate School of Education
Univ. of Calif., Los Angeles
Los Angeles, CA 90024

Dr. Kentaro Yamamoto
03-0T
Educational Testing Service
Rosedale Road
Princeton, NJ 08541

Frank B. Yekovich
Dept. of Education
Catholic University
Washington, DC 20064

Dr. Joseph L. Young
National Science Foundation
Room 320
1800 G Street, N.W.
Washington, DC 20550